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Risk implications of renewable support instruments: Comparative analysis of feed-in tariffs and premiums using a mean-variance approach

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ABSTRACT

Different support instruments for renewable energy expose investors differently to market risks. This has implications on the attractiveness of investment. We use mean-variance portfolio analysis to identify the risk implications of two support instruments: feed-in tariffs and feed-in premiums. Using cash flow analysis, Monte Carlo simulations and mean-variance analysis, we quantify risk-return relationships for an exemplary offshore wind park in a simplified setting. We show that feed-in tariffs systematically require lower direct support levels than feed-in premiums while providing the same attractiveness for investment, because they expose investors to less market risk. These risk implications should be considered when designing policy schemes.

Keywords: Mean-variance analysis; Offshore wind; Energy policy; Feed-in tariffs

1 INTRODUCTION

To reach their targets for electricity production from renewable energy sources, many countries will have to accelerate deployment rates and increase investment in renewable energy projects. In Europe, annual investment in renewable energy has to approximately double to about EUR 70bn, so that the binding 2020 targets can be reached (de Jager et al., 2011). As the electricity sector in most European and American countries is liberalised, investments are generally profit-motivated and delivered by private investors reacting to respective financial incentives. A major role of governments with targets for renewable energy is thus to provide adequate incentives for such investments. For this, governments often use financial support instruments such as investment grants, tax breaks, feed-in tariffs and quota obligations with tradeable certificate markets. The applied policy instruments shall be effective in achieving the targeted deployment at the lowest possible cost. To provide adequate financial incentives that balance between providing sufficient incentive for investment and avoiding high societal cost from support payments, it is essential that policy makers when designing policy schemes have similar considerations as private investors when preparing investment decisions.

Pure cost-benefit analyses, which are often the basis of policy decisions (Gross et al., 2010), are usually not sufficient for investors. One reason for this is that cost-benefit analyses only consider net benefit (or return) as key indicator for attractiveness of investment. This one-dimensional perspective can however lead to fatally wrong decisions as it does not inherently consider the risk of investment. This is illustrated in Figure 1, where project A would be preferred in a cost-benefit analysis due to the highest return, although project B is in fact more attractive as it has the best risk-return relationship.

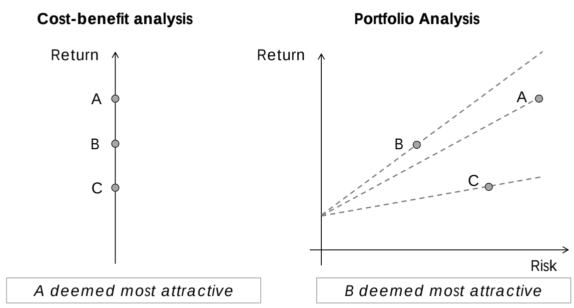

Fig. 1: Diverging conclusions of cost-benefit analysis and portfolio analysis for the same hypothetical projects A, B and C (Kitzing and Ravn, 2013)

The recognition that expected return and the related risk are the only two - and equally important - indicators relevant for private investment decisions is a cornerstone of modern portfolio theory (Markowitz, 1952). The underlying approach is often referred to as mean-variance portfolio approach (MVP) (or mean-standard deviation approach) as risk and return are represented in the quantitative analysis by the two indicators mean (expected level of return) and variance (of the expected level of return). According to modern portfolio theory, a typical risk-averse investor would always require higher returns for riskier investments. For our analysis this is relevant as some support schemes inherently expose investors to more market risk than others. These support instruments would (all other things equal) consequently require higher direct support levels to compensate for the higher risk. It is from this basis that we start our analysis.

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1.1 Literature review

The MVP approach has been applied in the energy area to a considerable extent. It was first used to optimise fossil fuel procurement in the U.S. regulated electricity industry (Bar-Lev and Katz, 1976). The work of Awerbuch (1993) and Awerbuch (1995) started a new interest in the field, especially for analyses of optimal generation mixes on national and regional level, including the U.S. (Humphreys and McClain, 1998), the EU (Awerbuch and Berger, 2003), Italy (Arnesano et al., 2012), the Netherlands (Jansen et al., 2006), China (Zhu and Fan, 2010), and for combined heat and power in Germany (Westner and Madlener, 2011). MVP has also been applied for fuels and electricity in the worldwide transport sector (Guerrero-Lemus et al., 2012).

Awerbuch focused in his work mainly on risk on the cost side, i.e. fossil fuel cost. Arnesano et al. (2012) and Jansen et al. (2006) have additionally considered risk on the supply side such as risk from uncertain resource availability, which is especially relevant for renewable energies reliant on wind or solar irradiation. Roques et al. (2006) and Roques et al. (2008) have pioneered the application of MVP for analysis from the perspective of (private) investors in the electricity sector. They broadened the scope of the analysis considering cost and revenue equally to analyse the full spectrum of incentives for investors.

In energy policy research, risk considerations play an increasing role (Mitchell et al. 2006, Wüstenhagen and Menichetti 2012). Different approaches are suggested, which are though mostly based on adding (more) risk elements into current cost-benefit approaches, e.g. by adjusting the discount rates or cost of capital (Gross et al. 2010, de Jager et al. 2008, Liebreich et al. 2011), by calculating a 'risk-adjusted' levelised cost (Levitt et al., 2011), and by using probability distributions in the net present value considerations (Falconett and Nagasaka, 2010). Approaches such as the MVP that handle risk inherently seem very suitable for the analysis of energy policy, and especially renewable support, as they give additional insights on the impact of uncertainties and risks for investors and society (as also briefly discussed in Wüstenhagen and Menichetti, 2012). Despite the interest in applying MVP in research on energy investments on the one hand, and the increasing interest in risk issues by energy policy research on the other hand, MVP has to the author's knowledge not yet been applied for the analysis of energy policy instruments and required support levels. This paper bridges that gap.

1.2 Research interest

The subject of investigation in this paper is to analyse the inherent relationship of risk and return for renewable energy under different support policies. A typical offshore wind project serves as case study, so that impacts on both the private investor (in form of attractiveness of investment) and society (in form of required support to be paid) can be quantitatively analysed in a concrete example. In principle, such analysis could be undertaken for any technology. Offshore wind investment is however a relevant topic in Europe as it has high deployment expectations but still relatively immature markets (Ragwitz et al., 2012). The decision on which support policy instrument to implement for offshore wind could be decisive for many countries in reaching their renewable energy targets.

In Europe, we see a recent trend to introduce Feed-in Premium (FIP) schemes for the support of renewable energy, either instead of or next to the previously more dominant Feed-in Tariff (FIT) schemes (seven EU countries have introduced FIP within the last decade, Kitzing et al. 2012). Combinations of FIT and FIT are implemented for example in Spain, where both schemes exist in parallel and producers can choose their preferred scheme (Schallenberg-Rodriguez and Haas, 2012).

We define FIT as schemes which provide guaranteed prices independent of the market price, where the support can be paid out either as 'fixed FIT' (the producer receives the guaranteed price in exchange for the produced power) or as 'sliding premium FIT' (the producer receives a sliding add-on to his sales on the market). The effect on income stability for investors is similar in both options. This definition of FIT is in line with Kitzing et al. (2012) and Couture and Gagnon (2010), but in contrast to Klobasa et al. (2013), who describe the sliding premium FIT of Germany as a FIP. FIP schemes are in our analysis fixed add-ons to market prices. In many applications of FIT and FIP in Europe, the support levels are predetermined by law and are not escalated with inflation (Couture and Gagnon, 2010).

Because of the rising interest in FIP and the tendency of European countries to move from FIT to FIP schemes, we analyse risk implications of these two policy instruments, rather than focus on quota obligation schemes, which have been analysed to quite some extent in the past, e.g. in Neuhoff and Butler (2008).

The focus of our analysis lies on the required direct support levels, which diverge because of the different risk exposures of investors. We do not consider indirect societal cost of renewable energies, such as integration or infrastructure cost. We acknowledge that such indirect effects can be substantial, as shown for integration issues in Lund (2005) and for infrastructure investment in Munoz et al. (2013) and Munoz et al. (2012). The risks associated with these costs should be considered in analyses that focus on the comprehensive evaluation of support schemes for society.

2 APPROACH: USING MEAN-VARIANCE PORTFOLIO THEORY TO INVESTIGATE SUPPORT POLICIES

In decision making, the relationship between risk and return is essential. Investment decisions are based on expected average returns (μ), which is almost always subject to risk of deviation over time - This risk is expressed in the variance (σ^2) or standard deviation (σ) of the expected returns (Markowitz, 1952). The higher the standard deviation, the broader the spread of possible return outcomes and thus the higher the risk. The deviation is usually in both directions, so the resulting return can be higher or lower than expected. Risk analysis is thus always connected to the willingness and capability of the individual investor to tolerate volatility of an uncertain outcome, and not only about the probability of lower than expected outcomes. In line with modern portfolio theory and most financial analysis, we base our analysis on the assumption that all investors have some sort of risk aversion, meaning that the higher the outcome volatility an investor has to accept, the higher return he expects (Markowitz, 1952).

An investor can influence some sources of risk more than others (e.g. operations more than weather), either by avoiding risk (e.g. through stringent planning), mitigating risk (e.g. through good project management) or hedging and insuring against the risk. This has been studied extensively, e.g. in Pousinho et al. (2011) who discusses an optimised way for trading wind energy under uncertainty. Common insurance products for renewable energy projects are mostly targeting technology and project risk (UNEP SEFI, 2004). In the context of MVP, hedging is important. Portfolio theory states that any investor can diversify his portfolio in a way that he does not have to bear risk other than the risk of the general market development ('systematic risk') (Brealey et al., 2008). Thus if an investor bears additional (unsystematic) risk, he does it voluntarily and should not be compensated for that. However, full diversification also requires that hedging is possible. For energy assets, it is not always likely that asset owners can find counter-parties with complementary risk attitudes. Roques et al. (2006) argue that electricity companies are likely to have to bear much of such cost of risk in their investment decisions.

In our analysis, we consider market risk as represented by the power prices. Additionally, we consider wind resource availability as a major source of risk for wind energy investments. Because wind resource availability is never fully predictable in terms of volume and time, it is difficult even in the medium to short term to hedge against volume risk through future contracts and therewith to stabilise income. We acknowledge that recently, innovative products such as insurance against average wind resource availability have entered the market in some countries (Williams, 2011), but we consider them still as being the exception rather than the rule.

2.1 Application and applicability of the mean-variance approach

The MVP approach has previously been criticised, see for example the discussion in Pézier (2011). Indeed, the applicability of MVP is subject to several restrictive conditions, such as that the returns must have a meaningful standard deviation. This means they have to be normally distributed or at least to have the same shape within a positive linear transformation (Pézier, 2011). This is by far not the case in all problems, and this condition can especially become an issue for complex structures such as an integrated energy system. Borch (1969) showed for example that in cases of stochastic domination, the MVP approach could lead to incorrect conclusions regarding the relative attractiveness of investments.

For our analysis, the stochastic variables (market prices and wind resource availability) considered should have characteristics of approximately normally distributed probability functions. This is a strong assumption of the approach. Our case data suggests that normal distributions are only acceptable as first approximation for the underlying data, as illustrated in Figure 2. Different approximations for probability functions have been discussed for wind power a.o. in (Carta and Velázquez, 2011) and (Villanueva and Feijóo, 2010), who favour Weibull distributions over normal distributions. Regarding electricity price modelling, normal distributions are often used as approximation (see Dixit and Pindyck 1994 and Conejo et al. 2010), although prices can exhibit extreme short term spikes. For a monthly consideration as in our analysis, the effects of spikes are less significant. For example an extreme spike of up to 2000 EUR/MWh that occurred during four hours in June 2013 in West Denmark caused the monthly price to be 21% higher than the year average (Energinet.dk, 2013). Such a price of 47.9 EUR/MWh is well within the range of our scenario simulations.

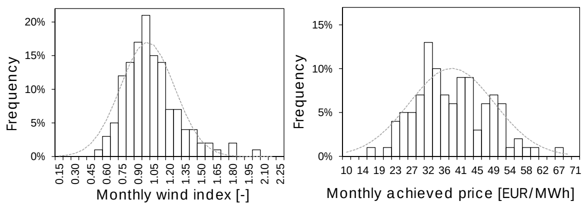

Fig. 2: Distributions of wind energy production and achieved prices in the analysed case

With the assumption of normally distributed variables, our subject of investigation stays within the boundaries as described by Sharpe: Our problem can be expressed as a case of 'adding a zero-investment strategy to an existing risk-less portfolio' (Sharpe, 1994). We base our case on an investor having a pre-existing portfolio that consists of a risk-less security, for which he considers adding an asset to increase the expected return (μ) while accepting a certain defined level of risk (σ^*). When choosing between two (mutually exclusive) investments X and Y, which are both risky assets, any risk-averse investor would choose the one resulting in the more advantageous risk-return relationship, which in the example is the combination of the risk-less security and asset X at risk level (σ^*), illustrated as $P_x X$ in Figure 3. Correlation is not relevant in this situation as the remaining holdings in the portfolio are risk-less (Sharpe, 1994).

The slope of the lines in Figure 3 is the Sharpe Ratio S (Sharpe, 1994). It sets the expected excess return of an asset $E[\mu - r_f]$ in relation to its standard deviation σ. Note that we use the excess return, i.e. the return above the risk-free rate r_f. The Sharpe Ratio thus measures how well an investor is compensated with return for a certain risk taken. In the example, the Sharpe Ratio of Asset X (S_X) is higher than that of Asset Y (S_Y). A higher Sharpe Ratio indicates a higher reward for assuming risk - and this makes an investment opportunity more attractive. Asset X in the example is thus more attractive to an investor. The Sharpe Ratio is in effect a proxy for risk-adjusted return (Dowd, 2000).

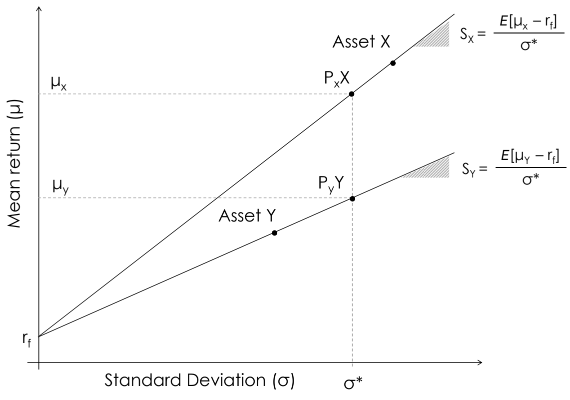

Fig. 3: Attractiveness of mutually exclusive investments, based on Sharpe (1994)

In our analysis the mutually exclusive investments as described above are 1) the wind park under a FIT ('Asset X') and 2) the wind park under a FIP ('Asset Y'). We compare the Sharpe Ratios of these cases and and then analyse the relative attractiveness of investment. From these results we determine the required support levels for each case. The resulting differences highlight one aspect of the comparative efficiency of the chosen support policy, namely the direct support payments. Other aspects (such as indirect cost) that would be important to evaluate policies in a comprehensive way cannot be covered by the mean-variance approach as applied in this analysis.

2.2 Return on asset as key parameter of the analysis

For the further MVP analysis, we have to specify the term 'excess return'. In previous applications in the energy area, different approaches have been used: Awerbuch and Berger (2003) use the reciprocal of electricity generation cost (kWh/cent) as return. Roques et al. (2008), more focused on the investor's perspective, use net present value (NPV) normed per unit of capacity. We have chosen to use a single-year Return on Asset (RoA) indicator, for which the net cash flows of a single year are divided by the overall investment in the asset. Our specific aim of analysis, i.e. to show the main relationship between risk and return for different policy instruments and the relative implications on support levels, can easily be shown on basis of a single year. A full lifetime approach including the investigation of effects from structural market changes is not in the scope of this paper. Further related research options are though discussed in section 5.

2.3 Calculation method

We have created a cash flow model for an exemplary offshore wind park in West Denmark. The cash flow analysis, created in Microsoft Excel (2010), uses Monte Carlo simulations to generate stochastic inputs, which are undertaken in the Oracle Crystal Ball (2013) extension. The resulting expected average returns and variances are the inputs for the subsequent mean-variance analysis using the Sharpe Ratio. For each set of simulations, we calculate the cash flows for the FIT and FIP schemes in parallel, meaning they use exactly the same random input variables in each simulation step, in order to avoid coincidental divergence of the results. The procedure for one set of simulations is illustrated in Figure 4.

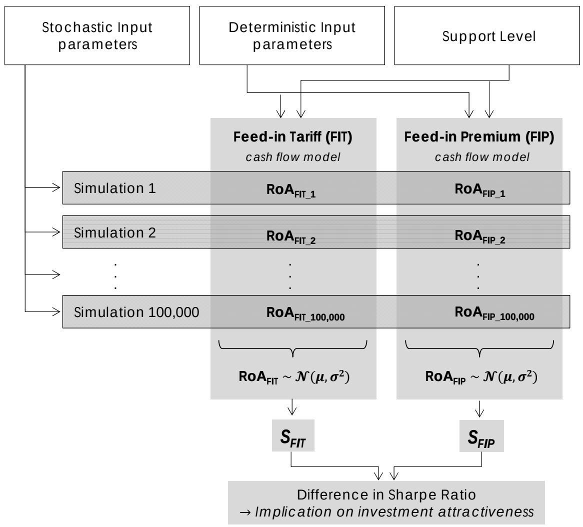

Fig. 4: Procedure for one set of simulations (repeated for each support level)

We let the model perform several different sets of Monte Carlo simulations, one for each possible support level. We then undertake additional sets of simulations for the sensitivity analysis, by variation of deterministic inputs (price level, production volume, investment and operational cost) as well as stochastic inputs (volatility of prices and production volumes).

3 DATA AND ASSUMPTIONS

The cash flows considered in this analysis comprise of a revenue part, which is income from sales on the market (spot power price) and income from the financial support scheme (FIT or FIP), and of a cost part, which is investment cost, Operation and Maintenance (O&M) cost as well as a balancing cost element. All elements except investment cost are in our (simplified) analysis dependent on the amount of electricity generated and thus on the available wind resource. Investment cost are considered sunk and thus fixed cost.

The time resolution is chosen as is most reasonable for the analysis. An analysis with yearly inputs only would be too simplistic because of seasonal variations of mean levels and volatilities especially for wind energy production volume. In order to capture short term stochasticity on a weekly, daily or even hourly basis, an approach different from a mean-variance analysis would have been appropriate. In the short term, production and market prices follow a path and could not have been modelled as independent normally distributed variables. In this case, a model based on e.g. random walks or Brownian motions would have been required, for example as undertaken in Kitzing and Schröder (2012). Such analysis can however not directly serve as basis for the MVP approach, so for the purpose of our analysis, we confine to a monthly basis for stochastic variations. At the same time, in order to correctly analyse the market revenues, we still need to consider hourly prices and production levels. For this, we use the indicator of 'market value' of wind, as described below.

The input parameters and assumptions were determined by a review of several sources using different units. For our purpose, all monetary values are converted to 2012 levels and Euro using inflation and exchange rate data from Statistics Denmark (2013). Unless otherwise specified, all monetary values are shown in terms of 2012 Euros.

3.1 Why an offshore wind park in West Denmark?

West Denmark is a showcase for offshore wind. By the end of 2013, West Denmark will have 810 MW of offshore wind power installed - in addition to 2.88 GW of onshore wind (Energinet.dk, 2012). This corresponds roughly to the normal maximum power consumption in the area, which is 3.7 GW. In recent years a considerable share of overall electricity demand has already been covered by wind energy, namely 34.9% (in 2011) and 38.1% (in 2012). Figure 5 shows the monthly average share of wind production as well as the range of minimum and maximum monthly production for the past nine years. Electricity generation from wind energy alone exceeded overall demand for a significant amount of time, namely during 226 hours (2011) and 342 hours (2012) (all based on data from Energinet.dk 2013).

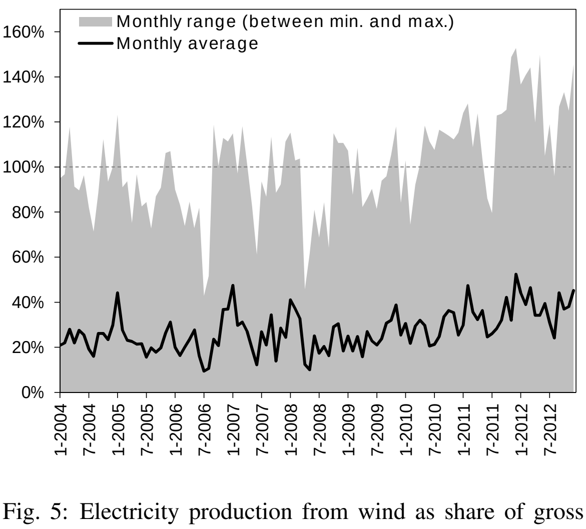

Fig. 5: Electricity production from wind as share of gross demand in West Denmark, based on data from Energinet.dk (2013)

3.2 Wind production volume and market prices

As average yearly wind production, we use 4003 MWh/MW for a normal wind year, which is an expected average for an offshore wind park installed in 2015 (Danish Energy Agency, 2012b). From historical production data 2004-2008, we can see that North Sea installations have achieved 4182 MWh/MW, which is approx. 4% higher, whereas inner seas installations in Denmark have achieved 3888 MWh/MW, approx. 3% lower (Danish Energy Agency, 2012b). The expected production volume is at an assumed full availability, so we (following the approach of Danish Energy Agency 2012b) only apply 96% of the gross production, i.e. 3843 MWh/MW per year or 320 MWh/MW per month, to account for non-availability due to breakdowns and planned maintenance periods.

We use a monthly index $I_{i,j}$ of offshore wind production based on the data provided by EMD (2013). We use this index rather than hourly production data directly, because EMD have, based on detailed hourly offshore production data, already matched production to the respective installed capacities in the area. The offshore wind production index for West Denmark exhibits a clear seasonal trend: Production tends to be higher in winter months with an equally higher variance, as illustrated in Figure 6.

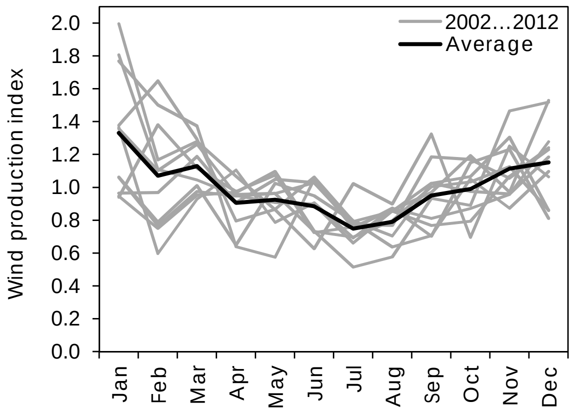

Fig. 6: Offshore wind production index, normalised to an average wind year in West Denmark, based on data from EMD (2013)

We derive the average monthly wind energy production $\overline{P}_j$ for the months $j = 1...12$ as simple average over the sample years $i = 1...m$:

$$\overline{P}_j \left[\frac{MWh}{MW}\right] = \frac{1}{m} * \sum_{i=1}^{m} \left(\beta * I_{i,j} * 320 \left[\frac{MWh}{MW}\right]\right) \tag{1}$$

where $I_{i,j}$ is the monthly index from EMD (2013). 320 MWh/MW is the monthly wind production of a normal year. The indices are multiplied by $\beta = \frac{1}{0.95}$, because the data basis of the years 2002-2012 exhibits an average index of only 0.95, which means that the data represent a period which was 5% worse than normal. To make the monthly indices fit with the production of a normal year, they are thus normalised by constant β. This has no influence on the volatility calculation. The related volatility $\sigma_{\overline{P}_j}$ is based on the standard deviation of the monthly index applied to the respective average monthly production:

$$\sigma_{\overline{P}_j} = \frac{1}{\overline{I}_j} * \left(\frac{\sum_{i=1}^{m} (I_{i,j} - \overline{I}_j)^2}{(m-1)} \right)^{\frac{1}{2}} * \overline{P}_j \qquad (2)$$

Table 1 summarises the wind production inputs used in the cash flow model.

As proxy for market prices, we use day-ahead spot prices for West Denmark as formed on Nord Pool (the common electricity market of the Nordic countries, Nord Pool 2013). The Danish electricity system is divided into two different synchronous zones (West and East Denmark), which are only connected by one interconnector. This division is also reflected in the Nord Pool Spot price zones. The prices in West Denmark tend to be somewhat lower than in East Denmark (Nordic Energy Regulators, 2012) and are more influenced by the Central European market. We assume the use of financial future contracts (traded up to six years ahead) to be limited due to the uncertain wind resource availability. Concerning intraday trading (on Elbas), we assume that wind parks participate there to mitigate balancing cost only. Balancing cost are included in the analysis as deterministic cost element only (see section 3.5).

In order to capture the correct revenues from the market for the wind park, we have to include hourly considerations, as both the prices and the production volume vary on a short-term basis. We do this by using the concept of 'market value' of wind, see also Sensfuss et al. (2007) and Hirth (2013). In this approach, historic data on hourly market prices and wind production is used to determine the average monthly price achieved by wind power production as compared to the average market price. We can then base our monthly simulation on the expected achieved prices of wind as opposed to the expected overall market prices. As long as there is no structural change in the price formation on the market, this indicator is a good proxy for the market revenue of wind.

The required hourly data is available for West Denmark for the years 2004-2012 from Energinet.dk (2013). In Figure 7, the market prices, the related achieved prices and the differences between the two are illustrated.

In general, the two prices are closely correlated. The prices achieved by wind are though systematically lower than the market average. For example in the years 2009-2012, the market value of wind was on average 6.3% lower than the average market price, varying between $+1.4\%$ and -21.8% on a monthly basis. This systematically lower value of wind can be due to different reasons. First of all, the wind patterns could be coincidentally so that more wind energy is produced during times in which market prices are low (off-peak periods). Another effect is experienced especially in markets with very high share of wind energy production where the wind production with its very low marginal cost is impacting the price formation on the spot market, pushing higher cost technologies out of the market. This effect is also referred to as 'merit order effect' (see Sensfuss et al. 2007), and has been shown to exist on the Danish market as early as for the year 2005 (Munksgaard and Morthorst, 2008).

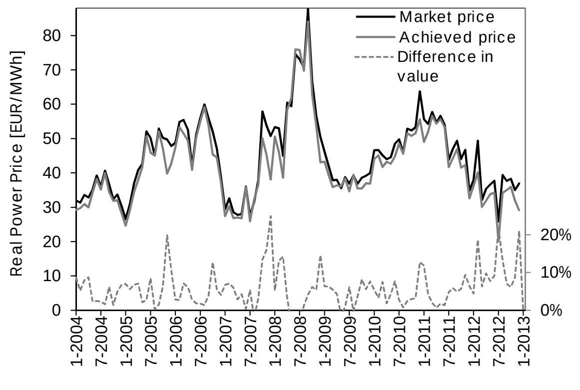

Fig. 7: Monthly average market prices and wind achieved prices, 2004-2012 in West Denmark, based on data from Energinet.dk (2013)

Trends from recent years with significant growth of offshore wind production in West Denmark (2009-2012) also support the assessment that the merit order effect may be correlated to the market share of wind energy (see Figure 8).

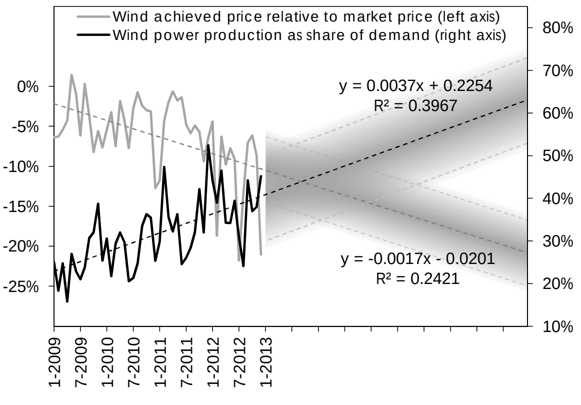

Fig. 8: Market value of wind and share of wind, historical data and trends for West Denmark, based on data from Energinet.dk (2013)

A further increase of wind production is expected in Denmark (up to an average market share of 50% already in 2020, according to the official Danish energy policy plan, Danish Energy Agency 2012a). With the approach taken in our analysis, we can simulate a possible future intensifying of this effect simply by lowering the input parameter 'wind achieved power price'. This is done in the sensitivity analysis.

We derive the average achieved price $\overline{\varphi}_j \left[\frac{EUR}{MWh}\right]$ for each month $j = 1...12$ as the average over the sample years

Table 1. Stochastic Input parameters for the analysis, average of years 2002-2012 (volumes) and 2004-2012 (prices)

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year
Production volume [MWh/MW]	Mean (μ)	426	343	362	290	296	284	240	253	304	317	357	369	**3,843**
	St.Dev. (σ)	122	108	50	49	48	50	39	34	63	52	58	79	**63**
	Coefficent of Variation (σ/μ)	29%	31%	14%	17%	16%	18%	16%	14%	21%	16%	16%	21%	**19%**
Market value of wind / achieved price [EUR/MWh]	Mean (μ)	37.1	38.7	36.6	38.4	39.1	44.1	39.1	42.9	44.5	42.6	40.2	36.7	**40.0**
	St.Dev. (σ)	6.7	6.6	6.2	3.6	4.6	4.2	8.0	4.3	5.6	7.4	5.7	7.2	**5.8**
	Coefficient of Variation (σ/μ)	18%	17%	17%	9%	12%	10%	20%	10%	13%	17%	14%	20%	**15%**

$i = 1...m$ of the weighted arithmetic means of the monthly revenues over the production:

$$\overline{\varphi}_j = \frac{1}{m} * \sum_{i=1}^{m} \left(\frac{\sum_{h=1}^{n} (P_{h,i,j} * p_{h,i,j})}{\sum_{h=1}^{n} (P_{h,i,j})} \right) \tag{3}$$

with h representing the hours of the month (e.g. in January from 1 to 744). $P_{h,i,j}$ $[MWh]$ is the hourly production volume for the respective month and year, and $p_{h,i,j}$ $\left[\frac{EUR}{MWh}\right]$ is the hourly spot price.

As shown in Equation (3), we use for each month an achieved price derived from the average real prices of historical years. The related volatility is the direct and simple standard deviation $\sigma_{\overline{\varphi}_j}$. We assume that market prices are not significantly altered when introducing a FIP. In our analysis, overall renewable production volumes remain the same in the comparative calculation, so market prices would only be affected in situations in which the sliding-premium FIT and the fixed FIP give different incentives to the sellers, i.e. extreme negative prices. Market price effects are thus expected to be limited. This simplification should nevertheless be kept in mind when interpreting the results. Table 1 summarises the price inputs used in the cash flow model.

3.3 Support schemes

For the modelling of support schemes, we use schemes similar to the ones applying to operating wind parks in Denmark. All large Danish offshore wind parks are currently supported by a tendered target-price feed-in tariff (as defined in Kitzing et al., 2012). This means that the FIT is paid out as a sliding premium between the guaranteed price and the market price. The different levels are illustrated in Table 2.

The FITs apply to 10 TWh (for Horns Rev 2 and Rødsand 2) and 20 TWh (for Anholt) of production, corresponding to

Table 2. Feed-in tariffs for three Danish offshore wind parks, converted to Euro from Danish Energy Agency (2009a)

	Tender	Guaranteed Price [EUR/MWh]	Support level [EUR/MWh] at market price of 40 EUR/MWh
Horns Rev 2	2004	69.53	29.53
Rødsand 2	2007	84.43	44.43
Anholt	2009	141.07	101.07

approx. 12-15 years of operation and are constant in nominal terms (Danish Energy Agency, 2009b). The price guarantee is implemented in form of a sliding premium, i.e. a variable add-on on top of the market price. The add-on is determined on hourly basis as difference of the guaranteed price and the spot price in the respective Nord Pool price zone. When spot prices are below zero, no support is paid out (Danish Energy Agency, 2009a).

For the alternative policy scenario we use a FIP similar to the scheme currently applicable to onshore wind in Denmark, which is a fixed premium of approximately 34 EUR/MWh paid out as add-on to the market price, also constant in nominal terms (Danish Energy Agency, 2009b).

A wind park operating under the FIT scheme is only exposed to one major revenue risk, namely uncertainty about production volume, i.e. the amount of electricity that can be sold at the guaranteed price. Under the FIP scheme, his revenues are subject to market price risk as well as to risk in production volume.

In our analysis, we test the risk implications of the two described support schemes for support levels between 0 EUR/MWh and 80 EUR/MWh, which is well above what is expected as support level for future wind parks in Denmark under a similar support scheme as the existing one (Deloitte, 2011). For FIPs, the support level corresponds directly to the guaranteed add-on. For FITs, the support level is calculated as the guaranteed price minus the market value of wind. For example a support level of 40 EUR/MWh corresponds to a FIP of 40 EUR/MWh on top of the market price (e.g. 50 EUR/MWh) and to a guaranteed price under the FIT of 90 EUR/MWh (including both the level of support and the market price). The same support level thus results for both schemes (FIT and FIP) in the same average income for the wind park and thus the same average RoA. The same support level also results in the same direct support payment burden to society.

3.4 Technology data

Estimates of technology cost differ significantly in publications about offshore wind parks. A description of current technological and economic developments in offshore wind technology can be found in Sun et al. (2012). Table 3 gives an overview of average figures as well as ranges of investment cost and O&M cost of some relevant studies. We apply mid range values for our base case and make sensitivities for all maximum and minimum values.

Table 3. Investment and Operation and Maintenance cost for offshore wind, all prices converted to real 2012

	Reference year and source	Investment [mEUR/ MW] Average	Investment [mEUR/ MW] Min - Max	O&M [EUR/ MWh] Average	O&M [EUR/ MWh] Min - Max
Empirical data	2002-2009 (operating parks), Danish Energy Agency (2012b)	2.2	1.4 - 2.8		
	2006, Morthorst et al. (2009)	2.4	2.1 - 2.8	18	
	2010 (German projects), KPMG (2010)	3.7	3.4 - 4.0	27	
	2010-2013 (planned parks), Danish Energy Agency (2012b)	3.2	2.4 - 3.9		
Forecast	2015, Morthorst et al. (2009)	2.1	1.8 - 2.4	15	
	2015, Danish Energy Agency (2012b)	3.2		19	
	2020 (market balance), Danish Energy Agency (2012b)	2.5		17	
Applied in this analysis		2.6	1.8 - 3.9	18	15 - 27

3.5 Other assumptions

As additional cost element, we apply a deduction of 5% on the achieved price to account for balancing expenses arising from wind forecast errors and trading. This deduction lies in the middle of the range of balancing cost identified for West Denmark by Holttinen et al. (2011).

As approximation for the risk-free rate, we use the analysis by Credit Suisse (2013), who have found that the average risk-free rate (approximated from the average interest rate of short-term government bills issued) between 1963-2012 was 2.7% in real terms. We choose such a long time horizon, so that our results are less influenced by short term developments such as the recent economic crisis. Equity risk premium in Denmark was 3.5% during the same time period (Credit Suisse, 2013). The overall real market interest rate can thus be approximated to 6.2%. We use this as benchmark in the further analysis.

3.6 Scope and limitations

Our analysis has some significant simplifications and estimations. We assume normal distributions for monthly wind power production and achieved market prices. We do not use a specific offshore wind park, but base our cost assumptions on average values only. This serves our purpose of showing a general relationship between risk-return and required support levels.

We do not consider inflation, which to our evaluation is not a significant issue because the analysis is based on a single year only. Inflation and especially inflation risk could be an interesting subject of investigation for future more long-term analyses.

Our study is based on a pre-tax analysis, so the resulting RoA should not be compared to usual after-tax company hurdle-rates. In general, taxes can be a significant element for consideration in investment decisions. Future studies going beyond showing the principle risk-return relations of different support schemes, should take this into consideration.

4 RESULTS

The results from the cash flow analysis show that for each level of support, the FIT and the FIP schemes result in the same expected mean RoA. At the same time, the FIT exhibits a lower variance of RoA than the FIP. Results of an exemplary set of simulations are shown in Figure 9.

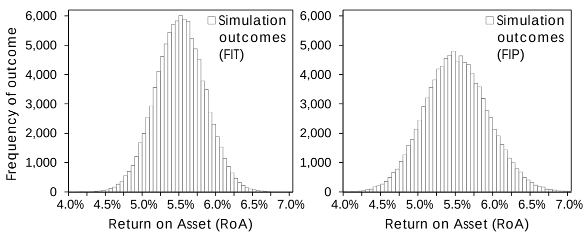

Fig. 9: RoA distributions for an exemplary set of 100,000 simulations (support level 15 EUR/MWh)

Figure 10 illustrates the resulting normal distributions for three different support levels. It becomes apparent that the differences between FIT and FIP are more significant for lower support levels than for higher levels.

Using the results of the cash flow analysis, we conduct the mean-variance analysis. Figure 11 shows the relation of mean expected return and risk for the two different support schemes at an exemplary mid-range support level. Here, the FIP scheme exposes the investor for the same mean expected RoA to more risk (the RoA has a higher variance), and its Sharpe Ratio is lower (which can be seen in the lower gradient of the line). The FIP is thus less attractive for an investor.

A government wishing to uphold the same attractiveness of investment under both policy support schemes (i.e. to keep the Sharpe Ratio constant) would have to provide a considerably higher support level under a FIP scheme than under a FIT scheme. The difference in required support level can be read from Figure 12. In the example indicated with dashed lines, the FIP scheme would require a market add-on of 35 EUR/MWh, which is 40% higher than the required support level under a FIT scheme (25 EUR/MWh).

The resulting Sharpe Ratios presented here may seem very high when compared to rates normally dealt with in financial analysis, where ratios of three usually already are deemed as very good investments. The reason for such high ratios

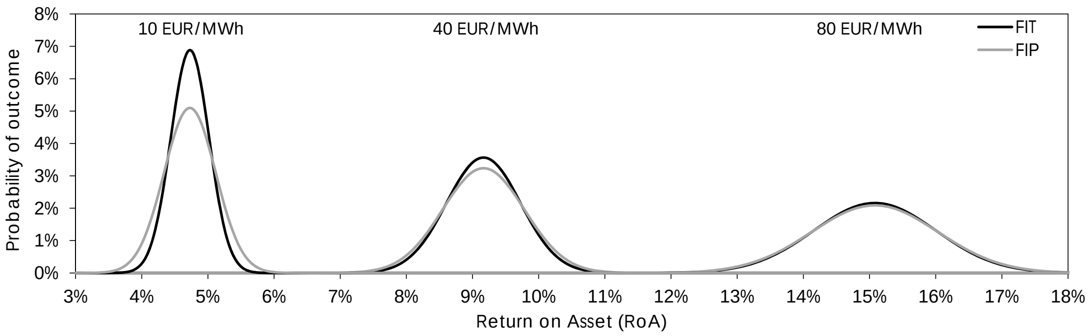

Fig. 10: Resulting normal distributions of RoA for support levels of 10 EUR/MWh, 40 EUR/MWh and 80 EUR/MWh

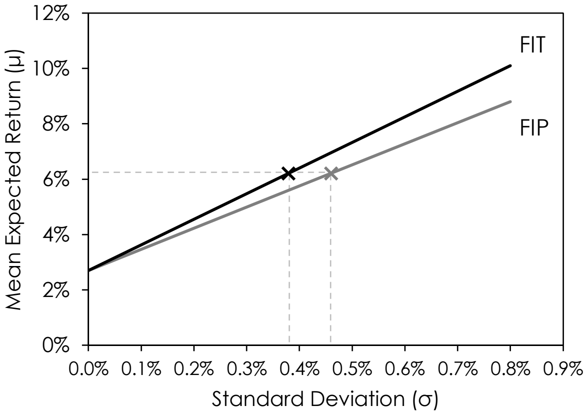

Fig. 11: Results of the simulations for the same mean, here with a support level of 20 EUR/MWh

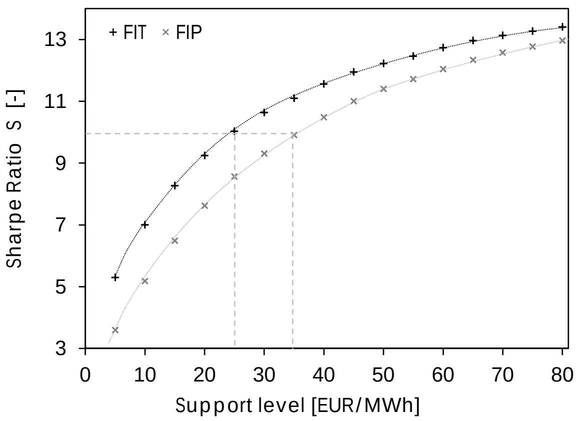

Fig. 12: Required support level dependent on the Sharpe Ratio, for the two support policy schemes FIT and FIP

lies mainly in the time frames we have chosen for the analysis. Usually, financial analyses would be based on more frequent and short term changes. For example market traded investments (such as stocks) may change their price many times each day, often with high volatility. Modelling the monthly volatility of electricity prices and wind volumes only, we have a different basis. Additionally, we investigate assets under a strong support scheme that reduces risk exposure of the investor significantly as compared to other (not supported) assets.

4.1 Sensitivity Analysis

We undertake sensitivity analysis on the most significant deterministic and stochastic inputs. The sensitivities are undertaken *ceteris paribus* towards the base case and are based on 10,000 runs per set of Monte Carlo simulation only to save time and data handling. The effects of this simplification have been tested and are minor.

The results of the sensitivity analyses are presented in graphs showing the difference in Sharpe Ratio between FIT and FIP schemes ($S_{FIT} - S_{FIP}$) at all investigated support levels. A positive difference indicates that the FIT is more attractive at a given support level. Results with a RoA lower than the risk-free rate (and therefore negative Sharpe Ratio) are not shown.

All sensitivities are constructed based on a range of variations derived from historical data. For example the production volume is tested for a 13% decrease as compared to base case, corresponding to the lowest annual production of offshore wind in Denmark during the investigated period (in the year 2010), and a 5% increase, corresponding to the highest level of offshore wind production yet seen (in the year 2007). Investment and O&M costs are varied with the ranges as shown in Table 3. The results of the sensitivity analyses on deterministic input parameters are shown in Figure 13.

Regarding the stochastic input parameters, we have tested the volatility of production volume and of achieved prices for the most extreme months in our data set. This means that we have created fictive situations in which all months of the year exhibit a similar variation than in the month with the lowest and the highest coefficient of variation, respectively (which are shown in Table 1). The results are shown in Figure 14. The higher the volatility in production volume, the lower the difference between the FIT and FIP scheme. This is because the FIT scheme reduces only risk on the price side and not the volume side. The higher the impact of the volume risk as compared to price risk, the lower the benefit. In contrast, with

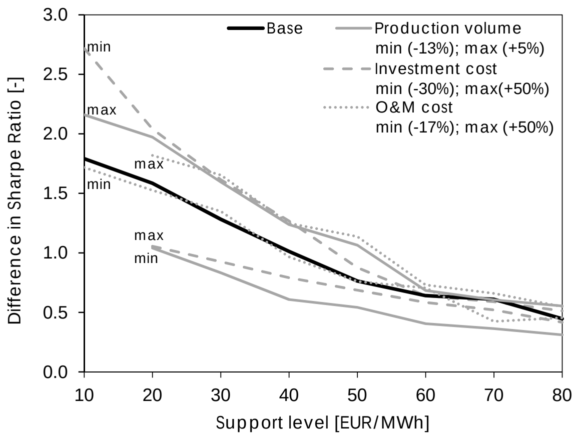

Fig. 13: Sensitivities on deterministic input parameters production volume, investment and O&M cost

increasing volatility of prices, the FIT becomes ever more advantageous over the FIP.

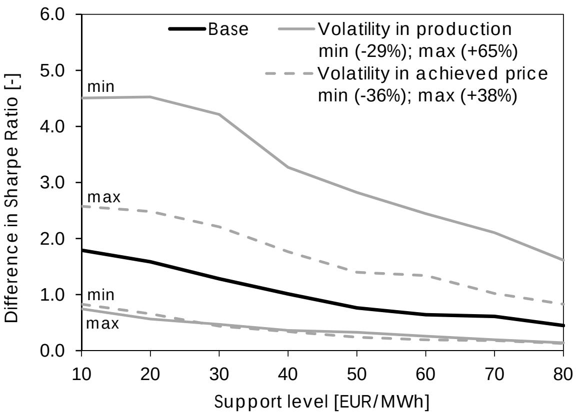

Fig. 14: Sensitivities on stochastic input parameters volatility in production volume and volatility in achieved prices

The sensitivity analysis for level of achieved prices as shown in Figure 15 is undertaken separately in order to account for the expected increase of merit order effect as described in section 3.2. We have tested for changes down to -50% (corresponding to an average achieved price of 20 EUR/MWh). For reference, we have also tested increases of the prices up to 80 EUR/MWh. The range of the sensitivities is well above what has previously been seen on the market, where the highest historical annual average price was in 2008 at 60.0 EUR/MWh and the lowest in 2012 at 32.7 EUR/MWh.

The results are rather sensitive to the assumed risk-free rate, because of the way the Sharpe Ratio is constructed. Sharpe himself discusses this in detail with a demonstrative example in Sharpe (1994). Figure 16 shows the sensitivity of results to a variation of the risk-free rate. The lowest risk-free rates result in the largest differences. The impact is largest for very low support levels. This is because at these low levels,

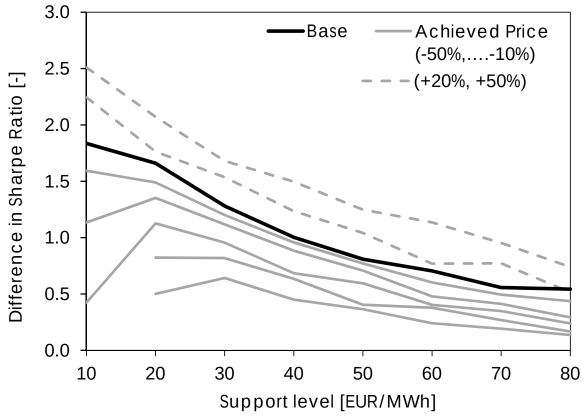

Fig. 15: Sensitivities on achieved price, variation between -50% and +50%

the risk-free rate dominates over the RoA (in the base case this is 2.7% as compared to 3.99% for a support level of 10 EUR/MWh) when determining the excess return (in the example only 1.27%), which is then divided by the standard deviation to arrive at the Sharpe Ratio. This effect reduces naturally with increasing support levels.

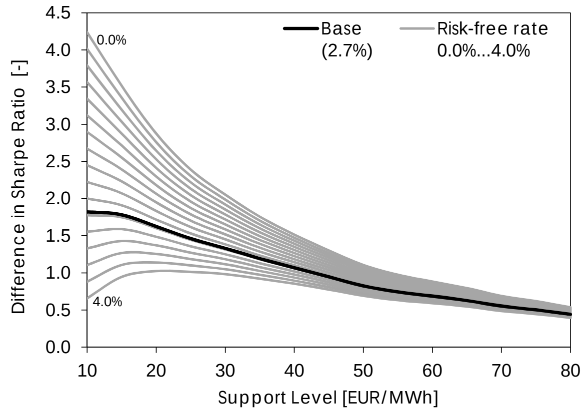

Fig. 16: Sensitivities on risk-free rate

We can conclude that two major characteristics of our results remain robust in all investigated cases. Firstly, the difference in Sharpe Ratios ($S_{FIT} - S_{FIP}$) is positive in all cases at all support levels, which indicates that for any given support level the FIT scheme is always more attractive for an investor. Secondly, we see a decreasing difference with increasing support levels, which implies that choice of policy instrument is especially relevant for low support levels.

5 DISCUSSION

The findings as presented above can help to improve policy design in terms of effectiveness and cost-efficiency. On the one hand, they give an indication of what policy makers could consider to better accommodate the needs of investors: If a policy scheme exposes investors to market risk, this should be acknowledged and investors should be compensated adequately for the risk taken. On the other hand, the findings can be used to avoiding windfall profits of certain policy schemes: If a policy scheme reduces risk for investors to a considerable amount, then investment can be attractive at relatively low support levels.

The simulations show that for the base case as well as for the sensitivities, the largest difference in Sharpe Ratio is for low support levels. This means that with technology progress and thus lower required support levels, it becomes more and more relevant to consider the risk implications of support schemes.

The results of this analysis are very much in line with the findings of Schallenberg-Rodriguez and Haas (2012), who showed empirically for Spain that wind energy investors required a 10-20 EUR/MWh incentive to move from the FIT to the FIP scheme. Our results are though seemingly in contrast to a recent analysis on the Nordic market by Kopsakangas-Savolainen and Svento (2013), who conclude that FIT would be more expensive for society. The major difference to our analysis is that Kopsakangas-Savolainen and Svento (2013) compare a predetermined FIT, which allows significant windfall profits for investors through inefficiently set support levels, with an 'economically sound' FIP. In our analysis, we calculate the required support levels at which the investors' return expectations are exactly satisfied, and therewith determine the 'economically sound' level for both the FIT and the FIP. Windfall profits would thus only occur, if the support is set at a level deviating from the one resulting from our analysis. The results can therefore not be directly compared.

In order to use the method as presented in this paper for concrete policy considerations under real market conditions, a systemic approach must be taken capturing structural market effects over time. This would require using an optimisation dispatch model that can forecast production and power prices for a complete energy system, and thus e.g. inherently incorporate the changes in the merit order effect of wind. Such research is already ongoing and preliminary results are published in Kitzing and Ravn (2013).

An issue that has not been analysed here is which policy instrument in general would be more favourable for society. For such an analysis, not only direct support payments, but also indirect effects (such as integration and infrastructure costs and their risks) need to be investigated. The results presented here show merely that risk implications should be considered when designing policies, otherwise significant unintended changes in investment incentive could occur, possibly leading to either unfulfilled deployment targets or windfall profits.

6 CONCLUSIONS

We have used a mean-variance approach to show that the choice of policy instrument for the support of renewable energy can have a decisive impact on the required support level and thus the effectiveness and cost-efficiency of the scheme. Choosing a policy instrument that exposes investors to more market risk requires higher support levels when the investment incentive shall be upheld.

Through cash flow analysis, Monte Carlo simulations and subsequent comparison of Sharpe Ratios for an exemplary offshore wind park in West Denmark, we have shown that feed-in tariffs generally require lower support levels than feed-in premiums while providing the same attractiveness for investment regarding the risk-return relationship. This is because risk-averse investors can accept lower returns when revenues are more stable. The difference in required support payments is in our case up to 10 EUR/MWh (or up to 40%). The sensitivity analyses undertaken for all major input parameters confirm the robustness of the results.

The focus of this paper was to principally show how the choice of policy instrument can impact the risk-return relationship of investments and what the implications for investment attractiveness and required support payments can be. The next step would be to use this insight for further investigations which include the analysis of effects from long-term market developments (including the merit order effect) and more specific investment opportunities. For now, we have shown that risk implications cannot be neglected in the design of policy schemes.

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